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Detecting Agitation and Aggression in People with Dementia using Sensors - A Systematic Review

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Abstract

Agitation and aggression are among the most challenging symptoms of dementia. Agitated persons with dementia can harm themselves, their caregivers or other patients in a care facility. Automatic detection of agitation would be useful to alert caregivers so that appropriate interventions can be performed. The building blocks in the automatic detection of agitation and aggression are appropriate sensing platforms and generalized predictive models. In this paper, we perform a systematic review of studies that use different types of sensors to detect agitation and aggression in persons with dementia. We conclude that actigraphy shows some evidence of correlation with incidences of agitation and aggression; however, multi-modal sensing has not been fully evaluated for this purpose. Based on this systematic review, we provide guidelines and recommendations for future research directions in this field.

Keywords: agitation, aggression, dementia, sensor, machine learning

1. Introduction

With an increase in the population of older adults around the world, the number of persons with dementia (PWD) has also increased significantly. Dementia is a syndrome that affects memory, thinking and cognitive abilities to

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perform activities of daily living [26]. As per a WHO report [20], there are currently 35.6 million PwD; this number will double by 2030 and triple by 2050.

Behavioral and psychological symptoms of dementia (BPSD) represent a heterogeneous group of non-cognitive type of symptoms and behaviours that occur in PwD [6]. BPSD are strongly correlated with the degree of functional and cognitive impairment and affect up to 90% of all PwD during the course of their illness. The most prevalent BPSD are apathy, depression, irritability, agitation and anxiety [6]. Agitation in the case of dementia is defined as “*inappropriate verbal, vocal or motor activity that is not judged by an outside observer to result directly from the needs or confusion of the agitated individual*” [9]. Agitation encompasses a range of activities, such as wandering, repetitive and purposeless behaviour, social inappropriate activities, and physically and verbally aggressive or non-aggressive behaviours [6, 10]. Similarly, aggression is a difficult symptom in dementia [12] and is defined as “*destructive actions directed toward persons, objects or self*” [27]. At least 25% of PwD experience agitation during the course of the disease [1]. Characterizing BPSD is a major issue and a number of observational methods have been designed to identify and assess their severity, such as the Cohen Mansfield Agitation Inventory (CMAI) [8]. However, these methods can be subjective, unrelated to the patient’s behaviour, and be influenced by caregivers memory or time spent with the PwD [26].

These behaviours indicate distress and confusion in PwD and increase the risk to injury to both the patients and the caregivers [2]. As documented increasingly in the literature and popular media (e.g. [4, 25, 5]), these agitated behaviours can lead to resident-on-resident violence and workplace violence towards staff in long-term care facilities. While statistics on resulting injuries and deaths are difficult to find, in British Columbia (Canada) for example, 16 patients have died in a period from 2012 to 2016 in nursing homes after physical confrontations that involved aggressive persons with dementia [25]. It is very difficult for the staff in a care facility (or a caregiver at home) to continually monitor the PwD. Therefore, automatic identification of incidences of agitation

and aggression in PwD would be an important tool to raise alarms to take appropriate interventions. Sensors potentially could be used to detect agitation and aggression. These sensors can be wearable, computer vision-based or ambient in nature. Different sensors can measure different modalities but also bring domain-specific challenges. For example, a wearable sensor may be taken off or turned off, cameras raise potential issues related to privacy, and ambient sensors may be tampered with by patients. In this paper, we present a systematic review of the techniques and studies for detecting agitation and aggression in PwD using different types of sensors. To the best of our knowledge, this is the first systematic review that looks into this research problem. In the next section, we present the methodology adopted to perform this systematic review.

2. Methodology

We conducted a systematic review search based on the research question: *Can we detect agitation or aggression in PwD using sensors to assess these behaviors.* We elaborated on the definition of ‘sensors’ to include wearable, camera, and ambient sensing modalities to expand our search. An information specialist conducted an extensive database search of Cochrane Central Register of Controlled Trials, Compendex, Embase, Inspec, Medline (Epub Ahead of Print, In-Process & Other Non-Indexed Citations, Ovid Medline daily and Ovid Mediline), PsycINFO, PubMed, and Scopus based on a combination of standardized database vocabulary (e.g., MeSH, Emtree) and keywords relating to 1) dementia, 2) aggression or agitation and 3) monitoring or sensors, such as cameras and pressure mat. A list of keywords used to search different databases is presented in Table 1.

The search for finding relevant papers was conducted in two runs. The first run contained search results from the inception of the databases to 23rd November, 2016. The literature search was performed again from November, 2016 to 31st March, 2017 to identify any additional publications that were published since the first time the search strategy was executed. Due to overlapping dates, the output of the search runs contained some duplicate studies that were

List of Keywords
Dementia, delirium, cognitive disorders, amnestic, organic brain disease / syndrome, cognitive defect, normal pressure hydrocephalus, shunt, benign senescent forgetfulness, huntington, aggression, violence, psychomotor agitation, agitation, hyperactivity, excitement, restless, monitoring, physiologic, signal processing, computer assisted, accelerometry, actgraph, vital signs, heart rate, wearable, sensor, machine learning, artificial intelligence, electrocardiography, electrocardiogram, wrist, worn, body, wireless technology, tape recording, video recording, video camera, pressure mat.

Table 1: These keywords and their variants are used to search different databases for relevant papers.

removed manually. All of the searches in both runs were limited to the English language only. The following three screening stages were performed that included title, abstract and full-text screening to find the relevant papers.

1. Screening 1 – Title Screening.

At this screening level, the following exclusion and inclusion criteria were used:

(a) Exclusion Criteria:

- Remove all non-human studies.
- Remove all studies on pediatrics, children and minors.
- Remove studies that use Psychiatric/psychological, medical, surgical and pure pharmacological interventions (no other devices involvement), treatment, management, assessment, administration, music/herbal/natural therapies for falls, brain injuries or body organs, cancer, pain, sleep, alcohol/smoking withdrawal, Autism, Schizophrenia, Parkinson’s disease, Delirium, Huntington’s disease, other neurological diseases.
- Remove studies corresponding to empty titles.
- Remove non-descriptive and uninformative titles, for e.g. “Forward”.

(b) Inclusion Criteria:

- Accept any human study that uses wearable sensor, actigraphy, smart home/hospital, EEG, ECG, Emotion or computer vision (or camera) for agitation, dementia or related disorders.
- Keep the studies if they include sensors used for people with dementia (irrespective of the intervention).

2. Screening 2 – Abstract Screening.

At this screening level, abstracts of the selected papers from Screening 1 were reviewed. Additional criteria were applied to exclude studies if they were:

- studies on pharmacological interventions with the use of sensors,
- studies focused on locomotion (i.e., steps taken, body activity, motor activity pattern),
- studies on general description or feasibility of a sensing device, for example, an actigraph,
- studies on other diseases such as Parkinson’s disease, ADHD, psychiatric disorders, mania, agitated depression, emotion recognition, apathy, patients with altered mental status, and emotion recognition,
- studies on diagnosis of dementia using sensing techniques or biomarkers,
- studies on sleep monitoring, sleep disorders, wake disturbances, disruptive nocturnal behaviors, sleep-disordered breathing, leg movements during sleep, mood swings, and depression,
- studies on the use of Socially Assistive Pet Robot (PARO),
- studies on Pharmacological intervention, e.g. measure effect of a particular drug on agitation using actigraphy,
- studies on children, care-giving aspects or abnormal activities,

- studies on discrimination between healthy controls and people with dementia,
- social and engagement studies on people with dementia, and
- other feasibility studies and review papers.

Two researchers (first and second author – SSK and BY) completed the first two stages of screening independently based on the inclusion and the exclusion criteria. Any records that were in disagreement were marked and discussed by the two researchers. After the title screening, both the authors, SSK and BY initially disagreed on keeping 8 studies as either relevant or not. After the abstract screening stage, both the authors, SSK and BY initially disagreed on keeping 2 studies as either relevant or not. However, the two researchers always resolved the conflicting records and reached 100% agreement. Therefore, a third reviewer was not involved in either of the screening stages.

3. Screening 3 – Full-text Screening.

The remaining records then underwent full-text screening. Studies were included after the full-text reviewing if they

- were conducted with PwD (irrespective of whether data analysis was performed).
- used simulated data to demonstrate a system or technique for detecting agitation / aggression in PwD.

One researcher (SSK) completed the full-text screening stage using the inclusion criteria.

2.1. Results

The two runs of the database using the keywords shown in Table 1 resulted in a total of 2,380 studies. The number of studies reduced to 1,725 after the duplicates were removed. In total, 1,639 studies were removed after the title screening. Then, the remaining 86 studies went to the second stage of abstract

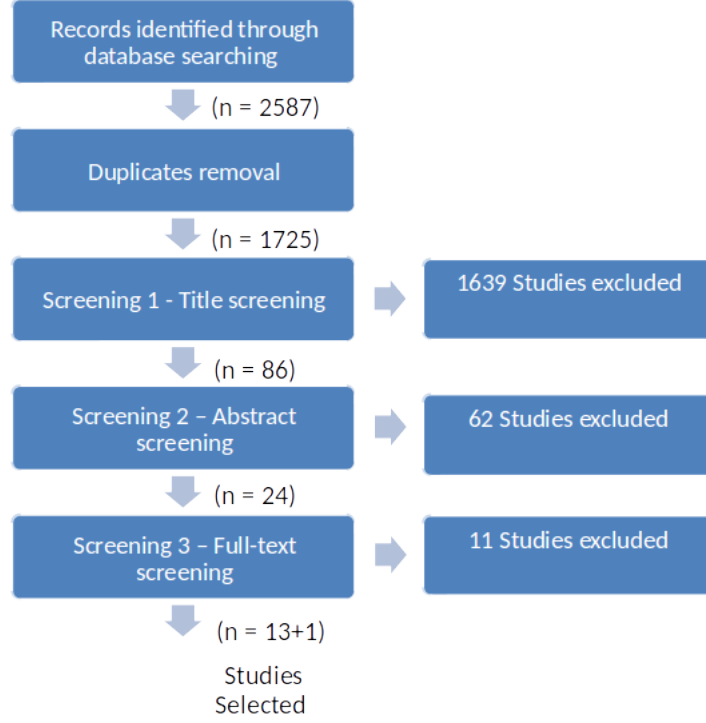


Figure 1: Work flow diagram for duplicate removal and the screening processes. ‘n’ is the number of papers after every screening stage.

screening with the additional exclusion criteria applied. Twenty-four studies were included for the full-text review. Among these, 13 studies were included for the final analysis. One more study was added based on cross-references (of the selected papers), which led to a total of 14 full text studies included in this paper. A diagram of the workflow for selecting the relevant papers is shown in Figure 1.

3. Literature Survey

We discuss the literature review based on three different sensing modalities: wearable, computer vision, and multi-modal sensing. Multi-modal sensing refers to a combination of wearable, and/or computer vision, and/or other ambient sensors to detect agitation and aggression in PwD.

3.1. Wearable Devices

Ghali et al. [16] performed one of the first studies on ‘sundowning’ syndrome in people with Alzheimer’s disease (AD) using a wearable device. Sundowning refers to increased agitation, restlessness and confusion among some individuals with AD during the later part of the day. They recruited 18 subjects and used a motion sensor that was placed inside a specially designed shirt worn over regular clothing. They collected raw data over 48-hour period from people with AD according to DSM-III-R criteria. They calculated the time at which peak activity occurred relative to local sunset time and as actual time of the day. They divided the collected data into three groups based on duration of illness, i.e. < 7 years, $7 - 10$ years, and > 10 years. A one-way ANOVA on two sets of mean times found sunset times were significant ($F = 0.86, p < 0.001$). Their results suggested that people with early AD showed increased activity before sunset, those with middle stage of the disease were more active around the time of sunset and those with advanced stage of the disease were more active after sunset.

Nagels et al. [19] conducted a study to examine the correlation between actigraphy measures and CMAI as the validated assessment scale of agitated behaviour in dementia. They recruited 110 subjects with different levels and types of dementia and AD. The participants were required to wear an octagonal basic motion logger on their non-dominant wrist. The actigraphs were affixed with plastic wraps so they could not be removed or re-affixed by the participants. The actigraph device collected information on three modes of activities: Zero-Crossing mode (ZCM), Proportional Integrating Measure (PIM), and Time-Above-Threshold (TAT). They found statistically significant differences in a two-factor (CMAI and MMSE) ANOVA design for PIM ($F = 126.75, p < 0.0001$ for CMAI; $F = 85.74, p < 0.0001$ for MMSE, interaction: $p = 0.0038$), ZCM ($F = 14.81, p = 0.0001$ for CMAI; $F = 163.01, p < 0.0001$ for MMSE, interaction: 0.0235), and TAT ($F = 28.34, p < 0.0001$ for CMAI; $F = 84.12, p < 0.0001$ for MMSE, no interaction). Their results showed high level of activities during the day for patients with high CMAI scores and low MMSE scores.

They found moderate but highly significant correlation between CMAI scores and actigraphic data.

Etcher et al. [12] presented an evaluation of activity-based data collected through actigraphy to identify complex biomarkers in PwD with and without aggressive behaviours. They extracted fractal dimension (FD)¹ and approximate entropy (AE)² from the actigraph data collected over two consecutive weeks. Reduction in both measures were associated with pathological rhythmicity [21]. They recruited 96 participants and divided them into two groups based on whether they had a history of aggressive behaviour (43) or not (53). Their results showed significantly lower AE values over 24 hour day period ($F(1, 94) = 9.236, p = 0.0003$) in people with aggressive behaviour ($M(S.D.) = 1.048651 \pm 0.199973$) versus non-aggressive behaviour ($M(S.D.) = 1.174354 \pm 0.202769$). The AE values were also significantly lower at nights ($F(1, 94) = 5.317, p = 0.023$) in people with aggressive behaviour ($M(S.D.) = 0.742755 \pm 0.190900$) versus non-aggressive behaviour ($M(S.D.) = 0.834131 \pm 0.194819$). The FD was significantly lower during the night ($F(1, 94) = 8.854, p = 0.004$) in the aggressive group ($M(S.D.) = 1.961885 \pm 0.166409$) versus the non-aggressive group ($M(S.D.) = 2.089971 \pm 0.239069$) but not during the 24 hour day period.

Valembois et al. [26] used wrist actigraphy to monitor apathy, anxiety, agitation and aberrant motor behaviour among older adults with dementia. Their study included 183 individuals monitored for 8 to 10 days, among whom 126 had dementia. Among these PwD, BPSD was more frequent and they found 8 cases with agitation. Their results showed that motor activity assessed by wrist actigraphy was significantly greater in patients with aberrant motor behaviour as compared to patients without it ($p = 0.04$). They showed no strong association between agitation and motor activity; however, wrist actigraphy was recommended to record motor activity to study BPSD in dementia.

¹Fractal dimension is a ratio providing a statistical index of complexity comparing changes between detail in a pattern and the scale at which it is measured [13].

²In the model for approximate entropy, runs of patterns are compared for a given time series. If these runs are similar in successive observations, it indicates low complexity, high regularity and smaller approximate entropy [21].

Seitz [24] recruited 20 individuals with AD who could ambulate independently with **actigraphs worn on their body** for one week. They divided individuals into two groups based on their CMAI scores as having high and low agitation. Their results showed strong correlation between mean motor activity of PwD and CMAI ($r = 0.74, p < 0.001$).

Bankole et al. [1, 2] used an **inertial wireless body sensor network** to continuously monitor movements of older adults with dementia over a long duration and identify occurrences of agitation from it. They recruited 6 people at high risk for agitation behaviour. **They placed the sensors at three sites on the body of the patients (dominant wrist, waist and opposite leg) for 3 hours.** The data was transmitted over a wireless network to a nearby data aggregator and manually annotated. Time and frequency domain analysis was performed and it was observed that Teager energy [18] correlated well with the annotated data. Their results showed [1]:

- association between sensor variables and CMAI,

Morning: correlation between three sensors and CMAI were, $r_1 = 0.28, r_2 = 0.35, r_3 = 0.36, p < 0.001$.

Afternoon: correlation between Teager energy and CMAI was $r = 0.42, p < 0.001$.

Evening: not confirmed for any sensor data.
- association between sensor variables and Aggressive Behavior Scale (ABS),

Morning: correlation between three sensors and ABS were $r_1 = 0.37, r_2 = 0.30, r_3 = 0.30, p < 0.001$.

Afternoon: correlation between only waist sensor and ABS was $r = 0.33, p < 0.001$

Evening: correlation between wrist sensor and ABS was $r = 0.24, p < 0.001$

They concluded that body inertial sensors have the potential to identify aggressive agitation in PwD. The results of their other study [2] were also similar.

3.2. *Computer Vision*

Fook et al. [15] presented a computer vision approach for recognizing agitation behaviour among PwD. They used a hierarchical features descriptor approach that learned primitive and intermediate features from the temporal segmentation maps of tracked patients using frame subtraction and skin segmentation techniques. Higher level features were then derived from these feature descriptors using fusion and reasoning. The first layer of the classifier consisted of a probabilistic classifier that could find decision boundaries associated with each agitation action (using Hidden Markov Models). The output of this classifier (likelihood values of test samples) was used as the input to a discriminative classifier, formally defined by a separating hyperplane (called as Support Vector Machine (SVM)). The second layer was intended to reduce inadvertent false alarms. The paper did not mention whether or not the experiments were conducted on healthy participants or PwD. This was the only study in our search that solely used computer vision to detect agitation/aggression in PwD.

3.3. *Multimodal Sensing*

Fook et al.[14] presented a design and implementation of a sensor fusion architecture for monitoring and handling agitation behaviour in PwD. The different sensors used in their framework were: ultrasound sensors, optical fiber grating pressure sensors, acoustic sensors, infrared sensors, RFID, and video cameras. Bayesian Networks (BN) were used to model the uncertainties of sensor measurements. Preliminary results suggested that fusing different sensors would require efforts in terms of developing a firmware architecture, but combining different modalities was useful to detect various types of dementia. However, their results lacked in terms of explaining the study, such as the number of patients recruited, demographic information, and protocols followed.

Qiu et al. [22] presented a multimodal information fusion approach to identify agitation incidences in PwD. The different sensing modalities they used were: pressure sensors, ultrasound sensors, infrared sensors, video cameras, and acoustic sensors. They extracted low level atomic features that represented

agitation and used a layered classification architecture that comprised of Hierarchical HMM and SVM. However, results from this study were based on mock up data created by simulation.

Rose et al. [23] employed wireless body sensors to study night time agitation, sleep and urinary incontinence in PwD. They used acoustic sensors placed near the bed, wrist worn sensors, a wireless identification and sensing platform, a tag under the mattress to estimate sleep quality, and a wetness sensor to record urinary incontinence parameters. They recruited 50 dementia participants and 50 caregivers. Data was collected over a period of 5 to 7 week nights in their homes. Results of this study were not discussed, as it appeared that the data was collected at the time their paper was published.

Gong et al. [17] presented a multi-modal sensing platform to discover the relationships between agitation during sleep and urinary incontinence in PwD. Their system consisted of three layers: sensing, base station, and cloud web server. In the sensing layer, they placed two accelerometers on the top and bottom of the bed to record movements, two Inertial Measurement Unit (IMU) nodes (gyroscope was turned off to save battery life) attached to the left and right wrist to monitor sleep agitation, a wetness detecting sensor on the bed to log urinary incontinence, and an acoustic sensor to record verbal agitation. Their system used a base station that used a cloud based health monitoring framework, Empath2 [11]. Furthermore, a cloud based server was implemented using a JAVA web application. Occurrence of agitation was estimated using Teager Energy based features by setting individualized thresholds. They deployed the system in the homes of 12 participants and the data was collected from 10 participants; the system failed to record data at one place and one participant withdraw during the study. They found that 12 agitation events detected by IMU devices were correlated with wetness events, and 10 sleep agitation events detected from bed sensor were also correlated to wetness events. Their results showed evidence of relationship between urinary incontinence and sleep agitation; however, all agitation may not be linked to urinary incontinence. In their study, it was not clear how the thresholds were set for detecting agitation.

Authors	Sensors	Data Analysis Methods	Demographic Information of Participants			Clinical Assessment
			#Males	#Females	Mean Age (years)	
Ghali et al. [16]	Motion	Statistical	3	15	78.8 ± 6.4	DSM-III-R
Nagels et al. [19]	Actigraphy	-	45	65	78 ± 8	CMAI, MMSE
Bankole et al. [1, 2]	IMU	Time, Frequency analysis	0	6	81.8	CMAI, ABS, MMSE
Etcher et al. [12]	Actigraphy	-	12%	88% ³	86.9 ± 6.6	MMSE
Valembois et al. [26] ⁴	Actigraphy	-	-	-	84.9	NPI, MMSE
Seitz [24]	Actigraphy	-	16	4	74.3 ± 8.69	CMAI
Fook et al. [15]	Camera	HMM, SVM, BN	-	-	-	SOAPD ⁵
Fook et al. [14]	Multimodal	BN	-	-	-	SOAPD
Gong et al. [17] ⁶	Multimodal	-	-	-	-	-
Qiu et al. [22]	Multimodal	HMM, SVM	-	-	-	SOAPD
Rose et al. [23] ⁷	Multimodal	Statistical	-	-	-	-
Belay et al. [3]	Multimodal	-	-	-	-	-
Chikhaoui et al. [7]	Camera and Accelerometer	Rotation Forest	6	4	-	-

Table 2: Summary of different reviewed research papers.

³Actual number of patients was not mentioned.

⁴Total of 183 subjects; their genders not specified.

⁵Scale for the Observation of Agitation in PwD [15].

⁶The system was deployed in 12 homes. Gender of participants were not specified.

⁷Total of 505 subjects; their genders not specified.

Belay et al. [3] proposed a system to collect data about the physical agitation of PwD, the natural living environments of PwD and their caregivers. They proposed to use body wearable sensors on PwD, acoustic sensors, light and temperature sensors, and motion sensors in the rooms. They presented a data framework to collect, extract and analyze complex data from different sensing modalities. However, this framework was conceptual and showed results on only simulated data.

Chikhaoui et al. [7] presented an ensemble learning method to detect agitated and aggressive behaviours using a kinect camera and an accelerometer. They recruited 10 participants that performed six agitated and aggressive behaviours. However, they did not mention if the subjects were healthy or PwD.

4. Results and Analysis

The results and analysis of this systematic review are presented in Table 2 and 3. Table 2 shows that:

- (i) Eight studies showed some evidence of correlation between actigraphy and agitation in PwD [16, 19, 1, 2, 12, 26, 24, 17].
- (ii) Only one study used video cameras to recognizing agitation behaviour in PwD [15].
- (iii) Six studies used multi-modal sensors for identifying agitation and aggression in PwD [14, 17, 22, 3, 7].
- (iv) Eight studies used various statistical and machine learning methods, such as HMM, SVM, BN, Rotation Forest, and Time and Frequency Analysis [16, 1, 2, 15, 14, 22, 23, 7]. The other six studies did not use any standard statistical or machine learning methods to detect agitation using single or multiple sensors.
- (v) Seven studies mentioned the demographic information of the participants in their studies, including their gender and age information [16, 19, 1, 2, 12, 26, 24].

(vi) Ten studies mentioned the various clinical assessment tools used to verify the results from predictive models [16, 19, 1, 2, 12, 26, 24, 14, 15, 22].

We performed a comprehensive analysis of the reviewed papers on the basis of following criteria:

- Did the study use statistical testing?
- Did the study report on the reaction of PwD to various sensors or account of user acceptability of sensing devices?
- Was the study conducted or limited to simulations?
- Whether the participants recruited in the study had dementia?
- Were the human subjects / ethics issues addressed?
- Was the study done in home or institutional setting?
- Was the study done in naturalistic or controlled setting?

Authors	Did they use Statistical Testing?	Did they report on the re-action of PwD to various sensors	Was the study conducted or limited to simulations?	Whether the participants had dementia?	Were human subjects/ethics issues addressed?	Was the study done in home or institutional setting?	Was the study done in naturalistic or controlled settings?
Ghali et al. [16]	Yes	No	Conducted	Yes	Not Discussed	Institution	Naturalistic
Nagels et al. [19]	Yes	No	Conducted	Yes	Yes	Institution	Naturalistic
Bankole et al. [1, 2]	Yes	Yes	Conducted	Yes	Yes	Institution	Controlled
Etcher et al. [12]	Yes	No	Conducted	Yes	Yes	Nursing Home	Naturalistic
Valembois et al. [26]	Yes	Yes	Conducted	Yes	Not Discussed	Institution	Naturalistic
Seitz [24]	Yes	No	Conducted	Yes	Not Discussed	Institution	Naturalistic
Fook et al. [15]	No	No	Simulated	No	Not Discussed	Laboratory	Controlled
Fook et al. [14]	No	No	Simulated	No	Not Discussed	Laboratory	Controlled
Gong et al. [17]	Yes	No	Conducted	Yes	Not Discussed	Home	Naturalistic
Qiu et al. [22]	No	No	Simulated	No	Not Discussed	Laboratory	N/A
Rose et al. [23]	No	Yes	Conducted	Yes	N/A	Home	Naturalistic
Belay et al. [3]	No	No	Simulated	N/A	N/A	N/A	N/A
Chikhaoui et al. [7]	No	No	Conducted	Not Discussed	Yes	Institution	Controlled

Table 3: Detailed analysis of reviewed research papers on different criteria. N/A means that the information for a given criteria is not available.

The results of this analysis is shown in Table 3, which suggests that:

- (i) All the actigraphy based (seven studies) reported statistical analysis of correlation between actigraphy and agitation, whereas only one study [17] that used multi-modal sensors reported such correlation.
- (ii) Ten papers reported conducted studies, and four papers used simulated data.
- (iii) Only three out of all the conducted studies discussed user acceptance of the sensing devices.
- (iv) Nine out of 10 conducted studies recruited PwD, four of them mentioned about ethics approval, eight of them were conducted in institutional settings and two in homes.
- (v) One of the conducted studies did not mention whether the participants had dementia or not [7].
- (vi) Among the conducted studies, 7 were reported in naturalistic settings and 3 in controlled settings.
- (vii) Two studies that used simulated data reported controlled experiments in laboratory.
- (viii) For simulated studies, information about ethics approvals, recruitment of PwD, place and setting of study were not available.

4.1. Discussion

Through this systematic review, we identify three areas of research for detecting agitation and aggression in PwD.

1. **Sensing.** Sensing relates to detecting events or changes in the environment. For the agitation detection in PwD, we notice that actigraphy is the most popular choice. The reason is that most actigraphy devices are easy to wear (like a watch) or attach to the body. However, we note from other

studies that multi-modal sensing is also a viable solution for this problem (see Section 3.3). Different modalities of sensing can capture different types of information. Multi-modal sensing is also important because if one sensing modality does not work for a specific reason, the other modalities can still capture relevant information. For example, if a person does not sleep on the bed equipped with pressure sensors (and rather sleeps on a couch, for instance), then an actigraph or camera may still capture that information. However, installing different sensors in the environment can have its own complexities. There are several challenges with using multi-modal sensing such as – installation of different sensors, synchronization of various sensors to record different parameters, software/firmware interface to transfer and store data in real-time to a base station, handling malfunctioning of different sensors, addressing privacy concerns, and acceptability by the persons using them.

2. **Clinical Study.** Once a proper sensing framework is installed, a clinical study needs to be performed to record data in PwD for further analysis. In our systematic review, we notice that some of the papers claim to develop their sensing environment for PwD; however, it is not clear from their results if they actually recruited PwD or healthy adults [3, 7]. A major bottleneck in these studies is the ethics clearance and recruitment of participants. Normally, ethics clearances require significant documentation and it is a time consuming task. The PwD cannot give their consent directly to take part in a clinical study; therefore, substituted decision makers need to consent on their behalf. If the study is going to be in a care facility or hospital, then the consent of caregivers and nurses is also needed. This can be a tedious and challenging task because all staff and residents need to consent before sensors could be installed. From a data collection perspective, consent refusal can be problematic because data has to be deleted manually for the corresponding non-consenting staff.
3. **Data Analysis.** After successful installation of sensors in the environ-

ment, ethics approval and recruitment of consenting participants, the next step is data collection and analysis. Since the patients' data are private, they have to be anonymized to preserve privacy and must be stored on secure servers with a backup strategy in place. Data annotation to mark ground truth labels is a challenging task. The researchers need to review nursing charts to note relevant incidents of interests (for e.g. agitation and aggression). The report charts may not follow a standard structure or a detailed description of the incident and the exact time of the incident may not be mentioned. From predictive modeling perspective, classification algorithms trained with noisy class labels may not yield generalizable models. Most of the papers we reviewed performed basic statistical analysis to find correlations between sensor readings and occurrence of agitation and aggression. This is useful as a first evidence to justify the rationale of using sensors. However, we may wish to predict or identify the occurrence of agitation and aggression in PwD. This would be useful to alert caregivers and prevent accidents from happening. The large amount of data coming from different sensor modalities contains a plethora of information and it is largely ignored in most of the studies. Proper data mining techniques followed by advanced machine learning methods are vital to build generalized predictive models to predict and identify agitation and aggression in PwD.

In this systematic review, we observed that some papers (e.g. [17, 3]) provided details on developing a sensor platform and system architecture, but either lacked in conducting a proper clinical study or subsequent data analysis. Whereas, some other papers performed a clinical study; they either used simplistic sensing (e.g. [19, 12, 26, 24]) or basic data analysis techniques (e.g. [1, 2]). The goal of most of these studies was to find relationships between agitation/aggression and sensing modalities; therefore, the predictive analytics component was minimal. From this literature review, it appears that there is some evidence on the correlation between different sensors and the occurrence

of agitation. The existing literature lacks in the development and clinical testing of a working system that is deployed in a real world setting and is capable of automatically detecting and predicting incidences of agitation/aggression in PwD.

5. Future Research and Conclusions

This systematic review shows that some clinical studies have been conducted to find correlations between different modalities of sensing and agitation in PwD. There are several future research directions to make these studies more useful and practical:

- Five out of 14 studies in this systematic review [16, 17, 23, 3, 7] did not use any behavioral or clinical assessment tools for dementia or severity of agitation. A good clinical study must employ such scales as a ground truth to verify and manually annotate incidences of agitation and aggression in PwD. A correctly annotated dataset is the key in building useful predictive models.
- There is some evidence to suggest that wrist actigraphy is acceptable to the users [26]; however, more studies are needed to test user acceptance in a multi-modal sensing environment.
- The validation of the technologies employed in a multi-modal sensing environment is among the most critical challenge. This goes beyond cross-validation with other assessment tools. A multi-sensory model trained and tested in one care facility may not work properly in another. This can happen as the number and types of patients may vary considerably, and because each facility's layout is different and that could lead to the deployment of different number and types of sensors. These issues can constrain the machine-learning algorithms in building generalizable predictive models. A major research focus should be on automatically transferring the learned knowledge from one care environment to another without compromising the accuracy of the predictive models.

- Data captured through sensor networks will potentially be very large. Therefore, best practices in storing and accessing big data must be employed. A major challenge is to securely store the private health information of patients. Researchers must verify from their respective ethics boards whether such data can be stored on cloud services; if not, then alternative secure storage devices must be deployed (with backup). Another challenge is the real time analysis of the data in deployment phase. If there are lags in the predictive modeling phase, it can introduce unnecessary processing delays that may compromise the utility of the underlying technology. In this systematic review, we already notice a cloud based health monitoring framework [11]. More analysis is needed to identify the deployment capabilities of such frameworks in real settings.

In this paper, we presented a systematic review of studies that use sensors to detect incidences of agitation and aggression in PwD. The review showed some evidence of correlation between actigraphy and incidences of agitation and aggression in PwD. We identified that sensing platform, clinical study, and data analysis are the three key factors that determine the success and usability of a study in this domain. We observed that non-invasive and multi-modal sensing is a plausible and useful research direction in this domain.

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